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Shop-floor scheduling as a competitive advantage: A study on the relevance of cyber-physical systems in different manufacturing contexts

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ABSTRACT

The aim of this paper is to analyse the relevance of cyber-physical systems (CPS) in different manufacturing contexts and to study whether CPS could provide companies with competitive advantage by carrying out a better scheduling task. This paper is developed under the umbrella of contingency theory which states that certain technologies and practices are not universally applicable or relevant in every context; thus, only certain companies will benefit from using particular technologies or practices. The conclusion of this paper, developed through deductive reasoning and supported by preliminary simulation experiments and statistical tests, is that factories with an uncertain and demanding market environment as well as a complex production process could benefit the most from implementing a CPS at shop-floor level since a cyber-physical shop-floor will provide all the capabilities needed to carry out the complex scheduling task associated with this type of context. On the other hand, an increase in scheduling performance due to a CPS implementation in factories with simple production flows and stable demand could not be substantial enough to overcome the high cost of installing a fully operational CPS.

1. Introduction

As companies adapt to a more customer-oriented market, they try to gain competitive advantage in their sector by incorporating promising emerging technologies and practices. Furthermore, some authors (Barney, 1991; Hitt et al., 2016) suggest that companies need resources that are difficult to imitate in order to achieve competitive advantage. Thus, to gain competitive advantage, some companies could elect to invest in a cyber-physical shop-floor as a strategic resource.

However, some promising new technologies and practices could be inapplicable to certain manufacturing contexts, limiting the performance gains of implementing such technologies/practices, as contingency theory has showed (Sousa and Voss, 2008; Weill and Olson, 1989). Contingency theory states that a lack of fit between a technology/practice and a firm's context can cause performance issues for certain companies, i.e., the environment and the structure of the company are not suited to incorporate a particular technology/practice.

A great example of this phenomenon of fit is shown in the work by Tenhiälä (2011), where a fit was found between the level of detail in capacity planning and the process type of a company. Tenhiälä shows that performing a 'finite-loading' capacity planning, i.e., scheduling, does not result in a good delivery performance in job-shop environments; whereas rough-cut capacity planning, a simpler and aggregated planning method, produced better delivery performance when applied in job-shop contexts.

On the other hand, certain technologies/practices could be applicable in every context and eventually turn out to be the standard for every business context, e.g., the internet. In this fashion, the proponents of the Industry 4.0 initiative (Kagermann et al., 2013) as well as some practitioners (Dalenogare et al., 2018) suggest that the integration of the Internet of Things into the manufacturing sector as Cyber-Physical Systems (CPS) could be one of those technologies/practices that prove to be the future standard in global supply networks, as businesses will incorporate customer demand information into their supply and logistics tasks and automated production factories, i.e., smart factories.

Although we agree with this vision that Industry 4.0 could be the new standard considering a supply chain scope, we think that when considering a more reduced scope, such as the shop-floor, the implementation and utilisation of CPS could be inapplicable for certain manufacturing contexts because not every shop-floor environment could

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significantly improve its performance by using CPS, offsetting the costs of a full CPS implementation.

Thus, the objective of this paper is twofold: to discuss whether the implementation and utilisation of CPS in the shop-floor level could result in an operational competitive advantage of a company and to hypothesise the fit between the manufacturing context and CPS capabilities where a competitive advantage could be gained through a better execution of the scheduling task. The conclusions of this paper will help practitioners to consider the expected benefits of utilising CPS in certain manufacturing contexts before investing in CPS and could serve as a starting point for an open and worldwide discussion regarding the actual performance gains in shop-floor operations using CPS.

The next section presents the approach used in this study to attain the aforementioned objective as well as the logical structure of the paper.

2. Approach and structure of the paper

Since the objective of this paper is to hypothesise the fit between the use of CPS and different manufacturing contexts to gain competitive advantage through the scheduling task, by taking full advantage of the investment in CPS, we have identified five steps needed to fulfil this objective, following the general structure of Tehniälä's (2011) study, as shown in Fig. 1.

Firstly, a characterisation of a cyber-physical shop-floor (CPSF) is needed to identify the enhancing characteristics that this technology could provide to the operations of a shop-floor and how these characteristics can support the scheduling task. Secondly, a description of the different manufacturing contexts existing in the industry and their scheduling needs is required to identify the best scenarios where a CPSF could provide the biggest performance improvement to overcome CPS investment costs. Thirdly, based on the capabilities that a CPSF could deliver to the manufacturing operations and on the scheduling needs that could be solved by these capabilities, a fit between the use of CPSF and manufacturing contexts is proposed by deductively identifying the context in which the scheduling needs solved by CPSF capabilities appear.

Fourthly, as full implementations of CPSF using particular scheduling techniques have not yet been reported, to the best of our knowledge, some related results supporting the proposed fit are analysed. Previous studies of actual implementations of CPS are reviewed and analysed to discover how the capabilities of CPS can help in a better execution of the scheduling task under certain manufacturing contexts. Moreover, in order to establish whether certain contexts could improve their performance through the scheduling task, some examples of real successful implementations of some production planning and control practices are analysed.

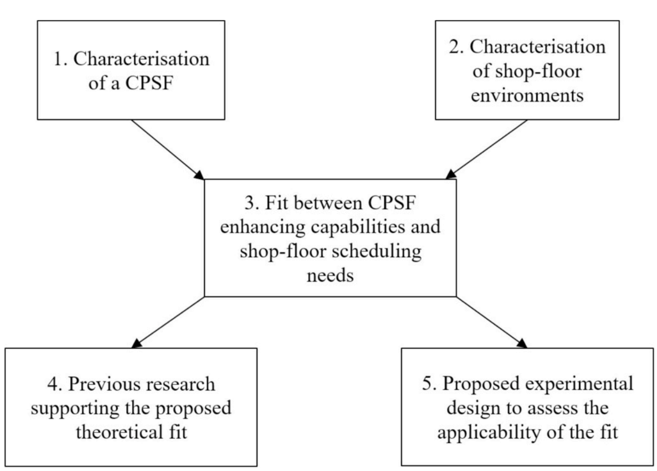

Fig. 1. Logical structure of the paper.

Finally, anticipating a prospective industrial environment where more CPSF are implemented, we propose an experimental design that will help researchers to assess the feasibility of the proposed fit. However, due to the limitations of the current industrial environment to empirically assess this applicability, we use this same design to investigate, through a surrogate simulation study, how some scheduling techniques that can only be carried out with the support of CPS capabilities, e.g., high level of monitoring and interconnectivity, have a significant influence in the performance of the shop-floor, depending on its manufacturing context.

Thus, the remainder of the paper is organised as follows. Section 3 describes the capabilities of a CPSF and how these capabilities can support the scheduling task. Section 4 presents some general concepts of Operations Management practice contingency research (OM PCR – Sousa and Voss, 2008) that will help identifying different manufacturing contexts. Section 5 discusses the possible fits between manufacturing contexts and CPSF implementation levels to gain competitive advantage, and proposes an experimental design, along with a preliminary simulation experiment, to assess the applicability of the fit. Section 6 presents the discussion and Section 7 the conclusions of this study.

3. The cyber-physical shop-floor

A standard and specific definition of a cyber-physical shop-floor (CPSF) is yet to be commonly used by practitioners and researchers alike (Weyer et al., 2015) as this technology is relatively new and there have been very few reports of implemented CPSF. Nevertheless, a number of authors concerned with supporting the Industry 4.0 initiative (Kagermann et al., 2013; Lasi et al., 2014; Monostori, 2014) as well as authors concerned with the design of cyber-physical factories (Lee et al., 2015; Scheuermann et al., 2015; Shi et al., 2011; Wright, 2014) agree in a number of characteristics and capabilities that any cyber-physical shop-floor should have. Next, we describe some of those characteristics:

- Production automation (Hernández and Mendoza, 2015) as a tool for manufacturing flexibility.
- Every physical component of the shop-floor and manufacturing process has a particular 'cyber' representation (Molina and Bell, 1999) embedded in the informational system; furthermore, the constraints that describe both the manufacturing processes and the characteristics of the production orders are also represented in the information system.
- An array of sensors to supervise and control the state of the physical components, manufacturing processes and production orders.
- A network communicating all the physical components with each other and with the manufacturing processes and production orders.

The combination of automated manufacturing equipment with an intercommunicated network, supported by technologies such as Internet of Things and RFID (Alqahtani et al., 2019), where all the constraints of the system are represented, would allow the cyber-physical factory to make autonomous decisions to improve the performance of the manufacturing process. Since the system is interconnected, scheduling decisions could be taken either by centralised algorithms or by decentralised heuristics without user interaction and then the schedule will be carried out autonomously in the shop-floor. Therefore, these new capabilities will provide shop-floors with the necessary tools to carry out the scheduling task in a dynamic environment (Rossit et al., 2018) and gain competitive advantage through an increased performance of the scheduling task.

Thus, a CPSF provides the technological environment where the scheduling task, as defined by Romero-Silva et al. (2015a), can be performed to its full potential because it is a fully automated shop-floor that can autonomously control production by implementing feasible production schedules (or updates/modifications to such schedules) as it has a full representation of the production process (the logic of the flow, the resources and their capacities, the materials needed for each task, and any constraint associated with each task/resource/material, e.g., sequence-dependent setup constraints and delivery dates). As it "understands" the full process and has full monitoring capabilities through sensors, a CPSF has relevant and updated information about the status of the manufacturing environment (job arrivals, work in process in each station, machine availability and efficiency), which is critical to build feasible schedules and identify potential conflicts with the current schedule.

In this regard, Fig. 2 shows how the CPSF is a platform integrating the physical shop-floor with the cyber-shop-floor through the process' sensors and monitoring activity, providing the foundation to carry out what some authors have defined as smart manufacturing/scheduling (Kusiak, 2018; Rossit et al., 2018). Smart scheduling will use the full capabilities of CPSF to gather all the relevant data, which is further processed into useable information, e.g., to predict future shop-floor workload, in order to inform the scheduling module (Framinan and Ruiz, 2010) and, using the automated control capability, to autonomously implement the feasible schedule into the physical process.

It is worth noting that the scheduling module in a CPSF environment can be either a decentralised entity sequencing jobs autonomously in each station or a centralised entity controlling the complete shop-floor by creating global schedules. The level of centralisation of the scheduling module would depend on the sensitivity of the tolerance problem, as defined by Rossit et al. (2018), which triggers a scheduling/-rescheduling task depending on how much the manufacturing environment has changed with recent events, such as, order arrivals, machine breakdowns, material replenishment delays, etc. For instance, a very dynamic environment with constant job arrivals, uncertain setup and processing times and high machine unreliability, would need several decentralised scheduling modules to be able to autonomously assign job sequences in each station, even though these decentralised modules could have global information because of the interconnectivity of the CPSF; whereas a more stable manufacturing environment would only need a centralised scheduling module to produce static schedules encompassing the complete shop-floor.

The proponents of the Industry 4.0 initiative expect that these previously described capabilities of the CPSF will allow companies to quickly adapt to changing market requirements in the form of new or customised products and different customer satisfaction goals, e.g., lead time and price, in order to gain competitive advantage, as productivity and resource efficiency increase in the highly competitive current business environment of mass customisation (Yin et al., 2018).

For a more thorough review of the literature concerned with Industry 4.0, the reader is referred to the work of Wang et al. (2015) and Lu (2017).

4. Contingency theory in OM PCR and characterisation of manufacturing contexts

The work concerned with contingency theory in Operations Management (OM) has been extensive as many authors have studied the applicability of different OM practices on different business contexts (Cheng and Farooq, 2018; Devaraj et al., 2001; Johansson and Olhager, 2006; Jonsson and Mattsson, 2003; Lloréns-Montes et al., 2004; McCarthy et al., 2013; Olson et al., 2013; Plugge and Bouwman, 2013; Salimian et al., 2017; Taylor and Taylor, 2014).

In addition, Sousa and Voss (2008) wrote a review of OM PCR where they showed that the strategic context of a company has been the most commonly used contextual (contingency) factor in OM PCR, followed by firm size and industrial sector. The strategic context of a company can clearly describe both the organisational environment and the organisational structure where the technology/practice will be applied and possibly find a fit (Romero-Silva et al., 2018).

One of the most commonly used representations of a strategic context has been the product-process matrix (Hayes and Wheelwright, 1979), where a natural fit between product variety and production process is described. Using the concepts of the product-process matrix, Helkiö and Tenhiälä (2013) extended the definition of strategic context to a more general definition by characterising the strategic contexts with three dimensions, namely, specificity of the production process, complexity of the production task, and dynamism of the task environment.

The specificity of the production process describes the degree of flexibility that production resources have to process different types of products. This dimension is described by the layout of the shop-floor, e.g., job-shop, manufacturing cells or assembly lines, and by the flexibility of the shop-floor to change product mix. The complexity of the production task is described by the degree of modularity that the products have and can be represented, for example, by the number of product families and by the typical bill of materials of a product.

Finally, the dynamism of the environment represents the rate of change of customer needs, of product introduction and obsolescence, and of manufacturing processes. The characterisation of a manufacturing context by these three dimensions can be very useful in describing the actual context of every shop-floor.

An additional work that is relevant in the topic of manufacturing contexts is the study by Wiers and Van der Schaaf (1997), where they present a classification of shop-floors according to the degree of uncertainty of the system and to the autonomy given to the workers of the shop-floor to cope with that uncertainty. Thus, they propose four types of shop-floors: smooth, socio-technical, stress and social.

The smooth shop has no uncertainty regarding job arrivals and has

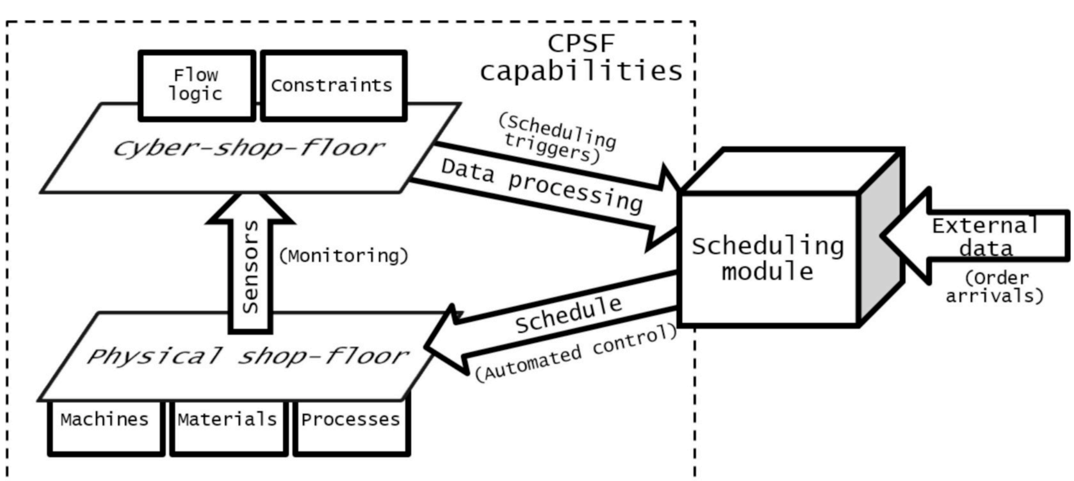

Fig. 2. Integration between CPSF capabilities and the scheduling task.

low production task complexity and high specificity of the production process, so it works with stable, optimised schedules without the need for shop-floor autonomy.

Contrary to the smooth shop, the socio-technical shop is a factory faced with high uncertainty as different types of jobs with different possible routings arrive constantly to the shop-floor, creating a difficulty in building a stable schedule. The socio-technical shop overcomes uncertainty by giving decision autonomy to the workers in the shop as they use simple heuristics, e.g., dispatching rules (Blackstone et al., 1982), to sequence jobs. In this context, the optimisation of operations is not needed as the market environment does not require tight delivery dates because most of the orders are engineered-to-order and the workload of the shop-floor, typically a job-shop, is not high, compared with its installed capacity.

The stress shop represents the conditions that some shops currently face in technologically-intensive markets since this type of shop faces high uncertainty with medium to high product task complexity and medium process specificity, i.e., a flexible or hybrid flow-shop. Moreover, they have tight delivery dates and stringent quality requirements. Therefore, the stress shop needs to find the best possible schedule to achieve market needs. Consequently, the stress shop needs to constantly reschedule their operations or implement flexible and reactive scheduling techniques to manage the shop-floor.

Finally, the social shop is a very special case of shop-floor where the context has low complexity but management decides to hand over some control to the workers in order to improve worker involvement and motivation (van der Schaaf, 1995). In this type of environment, the scheduling task is not a key factor in the performance of the company since the specificity of the process is very high (there are no alternative routings or resource assignments – a simple production line) and the complexity of the production task is very low (high modularity and/or few families of products).

A summary of some representative characteristics describing each shop-floor environment can be found in Table 1, based on the characteristics of 50 companies (Romero-Silva et al., 2015, 2016).

As it will be explained in the next section, we think that the stress shop is the manufacturing context where CPSF could find the best fit resulting in a competitive advantage for a company.

5. The fit between CPS and manufacturing contexts for competitive advantage

The lack of applicability of a cyber-physical shop-floor in certain manufacturing contexts could be caused by either a technological constraint or by the actual market environment of the company.

For instance, a significant number of companies currently lack the necessary infrastructure to install a CPSF as their processes are not automated, they lack an online system to supervise the current state of the shop-floor or they don't possess an intercommunicated network (see, e.g., Frank et al., 2019; Romero-Silva et al., 2016a). Nevertheless, this technological lack of fit could be overcome by investing in the necessary equipment and technologies to make the shop-floor ready for implementing a CPS (Schlechtendahl et al., 2015).

On the other hand, some CPS-ready companies could find that they will not gain significant competitive advantage after installing a CSPF since the actual performance gain could be minimal, compared with the overall costs of implementing a CPSF. This issue could be caused by a less than ideal fit between the strategic context of a company (described by process specificity, product complexity and environmental dynamism) and the characteristics of a CPSF. For example, a CPS-ready smooth shop, which is faced with little to no environmental and structural uncertainty because of a stable demand, a small number of different products/families and a linear production process, could only gain small improvements in their shop-floor operations (e.g., traceability of orders, online maintenance-related supervision) as their scheduling task is very simple.

Any manufacturing context that could benefit from implementing a CPSF would be a context that can fully take advantage of the characteristics of a CPS (automation, supervision, control, interconnectivity) to carry out a scheduling task that can manage the environmental and structural characteristics of the shop-floor in order to deliver a good performance. Both the complexity of the scheduling task and the actual manner in which the performance of the shop-floor is measured depend on the characteristics of the manufacturing context. In this regard, the capabilities of the CPSF will constitute the basic support for carrying out the scheduling task that arises from the needs of the manufacturing context, as seen in Fig. 2. Therefore, the context with the best fit with the

Table 1
Typical characteristics of shop-floor environments.

Environment Characteristics	Shop-floor environments: Smooth	Stress	Socio-technical	Social
Dynamism of arrivals	Low	Medium/High	High	Low
Number of products	Low	Medium	High	Low
Machine environment	Flow-shop	Hybrid flow-shop	Hybrid job-shop	Flow-shop
Due-date tightness	Not applicable (make-to-stock)	High	Medium	Low
Additional constraints	Permutation flow-shop	Sequence-dependent setup times	In-tree precedence, sequence-dependent setup times, sub-resources (special tools or operators)	

Table 2
Corresponding characteristics among CPSF, scheduling needs and context.

Primary contextual factor creating the scheduling need	Practical scheduling needs supported by the CPSF	CPSF capabilities supporting the scheduling task
Alternative routings from multiple products/families, e.g., hybrid flow-shops and hybrid job-shops	Implementation/execution of complex proactive and reactive schedules	Automation
Dynamic job arrivals, frequent shop-floor disturbances, stochastic processing times and changes in customer delivery needs	Continuous update of disturbances and of the status of the shop-floor	Supervision
Various constraints with multiple objectives	Generation, repair and update of 'tight' schedules to adjust for changes and reach objectives	Control
Dynamic job arrivals, shop-floor disturbances, e.g., machine breakdowns or blocking of stations due to high workload	Decentralised/localised decisions and communication	Interconnectivity

CPSF capabilities will be the context that has the scheduling needs that could only be fulfilled by having these capabilities, effectively creating a lasting intertwinement (Romero-Silva et al., 2018) between the structure given by the CPSF and the environment of the shop-floor.

Table 2 presents the roadmap to identify the manufacturing context with the best fit with CPSF capabilities by describing the scheduling needs that some CPSF capabilities could help solving, based on the characterisation of the practical scheduling task (Romero-Silva et al., 2015a). Moreover, Table 2 outlines the main contextual factors of a manufacturing context that could create these scheduling needs. For instance, a manufacturing environment with frequent machine breakdowns, dynamic arrivals and stochastic processing times creates the need for a continuous update of the status of the shop-floor in order to assess whether rescheduling is needed, which can be solved by the global supervision capability of the CPSF. It is worth noting that all these characteristics are not mutually exclusive and that various CPSF capabilities could solve different scheduling needs created by a number of contextual factors.

Taking these contextual factors into account, we think that the stress shop is the context that has the best fit with CPSF capabilities since its scheduling task will be highly dependent on a constant update, repair and implementation of schedules due to the manufacturing of different types of products/families with different possible routings and shop-floor configurations, e.g., flexible flow-shops or job-shops, and constant arrivals of new and different orders. Furthermore, the stress shop has very demanding customer requirements, such as, tight delivery dates, customised or engineered-to-order products, and strict quality conformance that requires efficient scheduling solutions.

The complexity of a stress shop could produce additional restrictions for the scheduling task, namely, sequence-dependent setup times (due to the variety of product families), assembly requirements, combined use of resources (e.g., machine tools and specialised workers), which result in an additionally complex scheduling task and an additional need for global supervision and control of shop-floor status.

A full implementation of CPSF would allow the stress shop to automate the scheduling task since disturbances and changes in the status of the shop-floor and on incoming jobs (Romero-Silva et al., 2015a) are supervised online. Therefore, reactive scheduling (Raheja and Subramaniam, 2002; Suwa and Sandoh, 2013; Vieira et al., 2003) could take place in moderately dynamic contexts where a centralised and complete schedule could be built by an appropriate scheduling algorithm (Allahverdi et al., 2008; Bagchi et al., 2006; Morton and Pentico, 1993; Pinedo, 2016; Ronconi and Birgin, 2012; Ruiz and Maroto, 2005) and carried out by the automated and controlled machinery. An example of this approach can be found in Ivanov et al. (2016) where a methodology is proposed for matching the monitoring and control tasks with the scheduling task through coordination and optimisation algorithms.

Stress shops with more dynamic contexts, on the other hand, can use decentralised techniques for dispatching and sequencing jobs on each shop-floor station because a centralised schedule will not be applicable in this type of environments. Methodologies such as order release (Bergamaschi et al., 1997; Fredendall et al., 2010; Mlinar and Chevalier, 2016) and sequencing rules (Blackstone et al., 1982; Lu and Romanowski, 2013; Münch et al., 2013; Terekhov et al., 2014) could be used to its full potential since some of those methodologies (see, e.g., Breithaupt et al., 2002; Mizrak and Bayhan, 2006; Rajendran and Holthaus, 1999) use global information of the shop-floor, despite being local decisions. As physical equipment, their queues, and the incoming job traffic are interconnected in the CPSF, every station will have the ability to take local decisions with global shop-floor information. This approach has already been considered by Liu et al. (2014) as they proposed to use a dynamic multi-priority sequencing procedure for node task sequencing in a CPSF.

5.1. Previous research supporting the proposed fit

Since the concept of CPSF and the technological means needed to implement a CPSF are recent, it is difficult to find actual implementations of scheduling techniques supported by CPSF capabilities (Wang et al., 2015). Thus, previous studies concerned with implementations of scheduling techniques in real manufacturing contexts, and studies regarding the implementation of CPSF are reviewed in this subsection to support our conjecture regarding the fit between CPSF capabilities and the stress shop.

For instance, Fuchigami and Rangel (2017) found, in a review regarding case studies in production scheduling, that almost half of the case studies were concerned with solving hybrid flow-shops problems, a machine environment that can describe the flow pattern of stress shops. Furthermore, they found that setup constraints were present in 42% of the cases where specific constraints existed, which is a constraint that is commonly found in hybrid flow-shop environments (Romero-Silva et al., 2016a) and which could create the need for building and implementing a complete schedule.

Moreover, Tenhiälä (2011) showed that, by carrying out 'finite-loading capacity' planning, i.e., scheduling, companies with flow-like production processes manufacturing various product families (stress shops) had the best performance, when compared with contexts with more complex combinations of product/process, e.g., job-shops, also using finite-loading capacity planning. However, they also found that scheduling with optimisation had the best fit regarding delivery performance with very simple production lines (smooth shops). In this regard, we argue that, despite the fact that smooth shops could clearly take advantage of executing a very detailed level of planning, smooth shops do not need the capabilities offered by CPSF as the scheduling context is simple enough to smoothly perform the scheduling task.

In addition, Tenhiälä and Helkiö (2015) showed that the supervisory and interconnectivity capabilities that ERP systems gave to manufacturing companies with dynamic contexts resulted in better delivery speed and reliability performance. Thus, Tenhiälä and Helkiö's results can be used as an evidence that CPSF capabilities, which are related with some ERP's capabilities, could enhance the performance of dynamic manufacturing contexts such as the stress shop.

Hendry et al. (2013) suggest that Workload Control (WLC) tools, which main objective is to stabilise and reduce the queue contents in the shop-floor through the use of order release and dispatching rules, are relevant in environments with dynamic arrivals, high variability of processing times, different and alternative routings, and no convergence of parts into an assembly, such as stress shop environments. WLC techniques also depend on CPSF capabilities to reach certain level of performance since they require a constant supervision of the queues in every station as well as a constant update of the jobs that will be released to the shop-floor. WLC additionally requires continuous assignments of alternative routings and job priorities to unload heavy-loaded queues and increase flow.

The study of Nilsen and Nyberg (2016) is one of the few studies, to the best of our knowledge, reporting actual implementations of CPS at the shop-floor level. According to their study, companies are currently using CPS capabilities for automatic supply of parts inside the plant, for communication and supervision among stations for assessing the correct execution of the schedule, and for a thorough consideration of its constraints, e.g., using aiding tools for accurate execution of production tasks, in environments where different products are manufactured. These findings show that CPSF capabilities could be used to support various types of tasks in environments where the production process is not completely repetitive and where some guides or instructions are needed to correctly complete the proposed schedule.

Finally, the study of Ayvarnam and Mayurappriyan (2017) showed that a 12% increase in productivity was attained in a company producing a wide variety of pumps for agricultural use by implementing some CPSF capabilities. This increase in productivity was reached by using the supervisory capabilities of a Manufacturing Execution System (MES) to carry out a well-informed process of order release and by the aid of a display to better convey all the scheduling instructions to the stations and workers in the shop-floor.

Therefore, these previously cited studies suggest that CPSF capabilities could be used to better support the scheduling task by enhancing the shop-floor capabilities of supervising and controlling the shop-floor and correctly conveying the schedule instructions to the shop-floor, resulting in a precise execution of the schedule. This correct schedule execution, in turn, will result in a better performance for environments producing different products or families of products. Despite the link found among CPSF capabilities, scheduling needs and product complexity by these studies, it is worth noting that these studies did not describe the specific production processes of the companies considered, so no link could be found in those studies between the specificity of the process and the implementation and use of CPSF.

These studies also showed that scheduling could provide performance gains and, consequently, competitive advantage, through better delivery speed and reliability (Christensen et al., 2007) in manufacturing contexts which can be categorised as stress shops. Consequently, these studies provide some evidence to support the conjecture regarding the fit between CPSF capabilities and the particular scheduling needs of stress shops, as shown in Table 1 and 2.

5.2. Experimental design to assess the applicability of the proposed fit

To assess the applicability of the fit between stress shops and full CPS, different combinations of environments need to be evaluated. Thus, various levels of implementation and use of CPS capabilities on different shop-floor environments need to be considered, as typical contingency theory studies in OM have previously done (Sousa and Voss, 2008; Tenhiälä, 2011).

Three levels of CPSF implementation are considered in this study, based on the levels of production data processing proposed by Mittal et al. (2018), namely, null, partial and full implementation; and only three shop-floor environments, as the scheduling task is not relevant in the social shop environment.

A full CPSF implementation entails having all characteristics of a CPS (automation, supervision, control and interconnectivity) in operation. Thus, the interconnectivity capability helps each station accessing the information of the entire shop-floor to take decisions using global and local information while the schedule is executed autonomously. A partial implementation implies that only some of the capabilities are operational, for instance, a shop-floor with a fully installed and operational MES system (Meyer et al., 2009) has supervision capabilities that could be used to carry some scheduling techniques with local information; however, the execution of the schedule in this context depends on a non-automatic release and completion of the schedule, e.g., some local agent such as a work-station operator. Finally, a null CPS implementation represents having no basic CPS capabilities.

In addition, the experimental design considers a threefold fit between CPSF implementation level, shop-floor type and the actual scheduling approaches carried out in the shop-floor, because even with a good fit between CPSF implementation level and shop-floor environment, companies could be applying scheduling approaches that do not take full potential of the actual installed CPS capabilities, effectively invalidating the proposed fit. Therefore, Table 3 shows the experimental design suggested to study the fit between CPSF implementation levels and shop-floor environments while also considering the most relevant scheduling approaches (Romero-Silva et al., 2016b; Vieira et al., 2003) per experimental setting.

It is worth noting that Table 3 assumes that companies use the best possible scheduling approach that could be executed based on the installed CPS capabilities. Thus, shop-floors executing the simplest possible scheduling approach without using any of the CPS capabilities will effectively be considered as companies with null CPSF implementation, irrespective of their actual technical CPS capabilities. In the same manner, shop-floors that only take advantage of partial CPS capabilities to carry out their scheduling task should be considered as companies with a partial CPSF implementation, irrespective of their actual installed CPS capabilities.

Moreover, the proposed fits marked with 'a' in Table 3 show the matches that provide the best trade-off between maximising performance and taking advantage of the investment on CPS capabilities. Fig. 3 illustrates the expected performance improvements per shop-floor environment that could be attained depending on different levels of CPSF implementation. Thus, although Fig. 3 (a) shows a negative slope for all shop-floor environments the higher the CPSF implementation level is, the steepest slope for the stress shop appears between a partial and a full CPSF implementation. Furthermore, the steepest slope for the socio-technical shop appears between null CPS capabilities and a partial CPSF implementation. Smooth shops, on the other hand, would not gain a significant performance improvement by any increase in CPS capabilities.

Fig. 3 (b), on the other hand, assumes a linear cost for increasing levels of CPSF implementation, whereas Fig. 3 (c) illustrates the best fit per shop-floor environment according to a weighted cost between the cost of CPSF implementation and a cost of customer dissatisfaction, considering that an increase in performance (decrease in the performance measure) will reduce the costs associated with customer dissatisfaction. Fig. 3 (c) can also be stated as the following hypotheses:

H1. *The relative increase in shop-floor performance, due to a better scheduling task execution, is dependent on the fit between the shop-floor type and CPSF implementation level.*

H2. *\Fits exist between particular shop-floor environments and specific CPSF implementation levels: stress shop with full CPSF implementation, socio-technical shop with partial CPSF implementation, and smooth shop with null CPSF implementation.*

To complete the experimental design, the responses of the experiments are associated with performance measures that result in competitive advantage for manufacturing companies and are dependent on the performance of the scheduling approach under a particular shop-floor environment. Typical performance measures that fulfil the two conditions are price (cost) and delivery performance (Li and Lee, 1994; Ray and Jewkes, 2004; Slotnick, 2011). Cost can depend on the utilisation factor of the production resources (or their idle time) and the

Table 3
Scheduling approaches per environment and installed capabilities.

	CPSF implementation level		
Shop-floor environment	Null	Partial	Full
Smooth	Static/predictive scheduling[a]	Predictive/reactive scheduling	Predictive/reactive scheduling with continuous schedule repair/update
Stress	Static/predictive scheduling or very basic WLC and sequencing policies	Predictive/reactive scheduling or intermediate WLC and sequencing policies	Predictive/reactive scheduling with continuous schedule repair/update or advanced WLC and sequencing policies[a]
Socio-technical	Rough-cut planning	Basic WLC and sequencing policies[a]	Advanced WLC and sequencing policies

[a] Indicates proposed fit between shop-floor environment and CPSF implementation level.

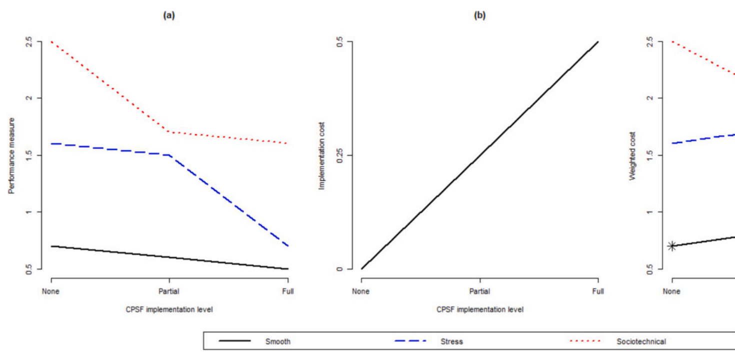

Fig. 3. Expected performance improvements and weighted costs per shop-floor environment depending on CPSF implementation levels, * indicates fit.

amount of work-in-process inventories, while delivery performance can be measured by either delivery date fulfilment rate or delivery speed.

On the other hand, various methodological approaches can be used to study this topic, depending on the availability of actual CPSF implementations. The most relevant methodological approach to thoroughly investigate the applicability of the proposed fit is the survey methodology since a big sample size of the performance of different shop-floor environments with different CPS capabilities will facilitate having empirically-based statistically significant results, similar to previous contingency-theory-based studies (Ahmad and Schroeder, 2002; Jonsson and Mattsson, 2003; Tenhiälä, 2011; Tenhiälä and Helkiö, 2015). However, considering the current lack of real full implementations of CPSF (Wang et al., 2015), the potential sample size of real implementations of CPSF could be very limited; therefore, multiple case-studies can also be used to assess the applicability of the fit, as other studies have done (Kemppainen et al., 2008; Zhang et al., 2007).

Moreover, an initial assessment of the fit can also be carried out in the 'laboratory', whenever access to real CPSF implementations is scarce, by carrying out simulations of shop-floor environments under different levels of CPSF implementation, which support different levels of scheduling complexity. Thus, models of theoretical or real shop-floor environments under different stages of CPSF implementation could be simulated to initially assess whether the proposed fit produces a significant increase in performance. This methodological approach is used in the current study since we wanted to carry out an initial assessment of the potential applicability of the proposed fit.

5.3. Simulation experiment to assess the impact of scheduling complexity on different machine environments

Since the industrial sector is currently in an initial stage of developing and implementing fully operational CPSF, a limitation exists in the number of available shop-floors with a full CPSF implementation. Due to this limitation, *H1* cannot be directly studied and we need to propose a surrogate hypothesis in order to study the influence that the fit between the shop-floor environment and the CPSF implementation level has on shop-floor performance due to a better execution of the scheduling task.

Based on Table 3, we designed a set of experiments that consider different WLC and sequencing policies supported by specific levels of CPSF implementation, applied under different machine environments. Therefore, we selected the factor of machine environment as a surrogate factor for shop-floor environment, as there is a general association between both variables, e.g., the stress shop with a hybrid flow-shop environment (see Table 1). Moreover, the degree of complexity in scheduling approaches, e.g., WLC and sequencing policies, is used as a surrogate factor to represent the support of CPSF implementation levels on the execution of the scheduling task since highly complex policies cannot be executed without full CPSF implementations and moderately complex policies cannot be used in shop-floors with null CPSF capabilities.

However, contrary to the proposition of Table 3, we considered the same scheduling approach for all the machine environments. This design allows analysing whether some machine environments are more 'sensitive' than others, in a statistical sense, to minimal changes in the scheduling approach applied. A positive result regarding this issue, i.e., *the impact of different complexities scheduling approaches on the performance of some particular machine environments is in fact more significant than in other machine environments*, will provide a solid motivation to further study the proposed fit in practical settings (see Table 3). Taking into account these considerations, *H1* can be restated in the following manner:

H1S. *The relative increase in shop-floor performance, due to a better scheduling task execution, is dependent on the fit between the machine environment and the complexity of scheduling approaches.*

Thus, the shop-floor environment is represented by the machine environment in this surrogate experimental setting, whereas the CPSF implementation level is represented by the complexity of the scheduling approach, as complex scheduling approaches cannot be carried out without a high CPSF implementation level.

5.3.1. Experimental design

As previously mentioned, two principal factors were used in the experimental design, namely, the machine environment and WLC/sequencing policies. Three WLC policies were selected with varying levels of informational needs: FIFO, ORR and PBB. In addition, four typical sequencing policies, i.e., dispatching rules, were selected according to their increasing informational needs: FIFO, SPT, SLACK and RR. The reader is referred to the work of Philipoom et al., (1993) and Rajendran and Holthaus (1999) for a thorough explanation of the selected WLC policies and dispatching rules, respectively.

Table 4 shows the values of each experimental factor. It is worth mentioning that the factors of WLC and sequencing policies as well as the factor of CPSF implementation level all correspond to only one factor that has been operationalised as the *policy complexity* factor, which measures the amount of information that the installed CPS capabilities are providing to the policies. Thus, a policy complexity of '1' entails having only a singular attribute of information (Branke et al., 2016) in

Table 4
Experimental design factor levels for the simulation model.

Factor	Low value	Intermediate value	High value
Machine environment	Flow-shop	Hybrid Flow-shop	Hybrid Job-shop
WLC policy	FIFO	ORR	PBB
Sequencing policy	FIFO	SPT and SLACK	RR
CPSF level *(Policy complexity)*	Null *(1)*	Partial *(2)*	Full *(4)*
Due-date tightness	TWK = 2		TWK = 3
Machine utilisation	85%		95%

the policies while a complexity of '2' means that the policies include two attributes in their formulas, and so on. Because of this characteristic, we made a minor modification to the ORR index so it models a policy complexity value of 2:

$$R_j = D_j - k_1 \sum_{i=1}^{n} p_{ij} \tag{1}$$

where.

R_j is the release date of job *j*,
D_j is the due-date of job *j*,
k_1 is the planning factor associated with the total work content, and
p_{ij} is the processing time of operation *i* of job *j*.

Notice that the original term describing the actual work content of all the queueing jobs in job's *j* path was not included because that would entail having an additional attribute considered in the policy, increasing the policy complexity and, consequently, the level of CPSF implementation.

Based on this experimental design, *H2* can also be restated with the following surrogate hypothesis:

H2S. : *Fits exist between a specific machine environment and a policy complexity: hybrid flow-shop with policy complexity 4, hybrid job-shop with policy complexity 2, and flow-shop with policy complexity 1.*

Furthermore, Table 5 shows the parameters used in some of the elements of the simulation model. Each product family had different mean processing times, which were modelled as a random variable using the lognormal distribution. Thus, the term *average processing time*, shown in Table 5, represents the average of the mean processing times of all product families. Each product family was randomly assigned a mean processing time that oscillated around the average processing time. The actual parameters of the lognormal distribution, i.e., μ and σ, for each product family, resulted from the previously assigned mean processing time and a predefined coefficient of variation of 0.27, which is the typical variability that could be found in some real manufacturing processing times (Slack, 1982).

Five typical scheduling responses (Blackstone et al., 1982; Rajendran and Holthaus, 1999) were considered to measure the impact on performance: % of jobs delivered after due-date (%tardy), mean flowtime, mean lateness, maximum flowtime and maximum lateness.

ANOVA tests were conducted to assess the influence that all factors had on all performance measures. Finding a statistically significant effect of the interaction between machine environment and policy complexity will suggest supporting the statement of *H1S*.

Table 5
Parameters of some elements of the simulation model.

Element	Parameters
Flow-shop	10 single-machine workstations, 1 product family, average processing time = 10[a], all product families with the same routing
Hybrid flow-shop	10 workstations, 2 machines per workstation, 20 product families, average processing time = 20, all product families with the same routing
Hybrid job-shop	10 workstations, 2 machines per workstation, 100 product families, average processing time = 20, all product families with random routing but with one and only one visit per workstation
ORR	$k_1 = 5$
PBB	T = 200 for flow-shops when utilisation = 0.85 T = 300 for flow-shops when utilisation = 0.95 T = 300 for hybrid flow-shops and job-shops when utilisation = 0.85 T = 200 for hybrid flow-shops and job-shops when utilisation = 0.95

[a] The average processing time of flow-shops was 10, instead of 20, to balance the workload per station throughout all machine environments, as hybrid shops were modelled with 2 machines per workstation.

Simulation runs were carried out using Simio 9.147 (Kelton et al., 2014). Run length per replication was 100,000 time units with 10,000 time units of warm-up period (Welch, 1983); whereas 100 replications were run per experiment. R 3.4.4 (R Foundation, 2016) was used to perform statistical analysis.

5.3.2. Experimental results

ANOVA tests (Table 6) show that all main factors have a significant effect on all responses (maximum lateness results are not shown because they are very similar to the results of maximum flowtime). Moreover, the effect of the interaction between the machine environment and the policy complexity (ME*PC in bold in Table 6), which is the most relevant effect for this study, is highly significant for all the responses, especially for %tardy and mean flowtime. This result suggests that performance is in fact influenced by particular combinations between machine environment and policy complexity, supporting *H1S*.

To further study the interactions between the machine environment and policy complexity, Fig. 4 shows the average results of %tardy, mean flowtime and maximum flowtime. Fig. 4 (a) illustrates how a simple flow-shop is not highly influenced by varying levels of policy complexity when considering the performance of % of tardy jobs, whereas hybrid environments significantly improve performance when a more complex combination of WLC/sequencing policies is used. Furthermore, the line representing the hybrid job-shop environment in Fig. 4 (a) – dotted line – shows a similar behaviour to the performance improvement predicted for socio-technical shops in Fig. 3 (a): the biggest improvement is attained between a small value and an intermediate value of policy complexity.

Additionally, Fig. 4 (b) suggests that the more complex the machine environment is, the more its performance regarding mean flow-time is influenced by increasing levels of policy complexity. It is worth noting that the line representing the performance of the hybrid flow-shop environment in Fig. 4 (b) – dashed line – shows a similar behaviour than the one predicted in Fig. 3 (a) for stress shops.

Finally, to test *H2*, a regression analysis on the responses was carried out, where the machine environments and policy complexities were operationalised as binary variables to assess the independent influence that each machine environment and policy complexity value had on performance. Furthermore, when the experiment contained the proposed fit between machine environment and policy complexity, characterised in *H2S*, a new binary factor called *FIT* was assigned a value of 1 to represent that the experiment had a fitting policy complexity with a machine environment (similar to Tenhiälä, 2011); otherwise, when the experiment did not contain a fit between these two factors, *FIT* = 0. A statistically significant coefficient in the regression analysis for the factor *FIT* would entail that fitting factors are significant in the performance of the shop-floor.

Table 7 shows the results of the regression analysis including only experiments with TWK = 2, in order to consider experiments with tight due dates and, therefore, relevant values for %tardy and mean lateness. Table 7 shows how all of the regression estimates for ME and PC values are significant at $p < 0.05$, with few exceptions, i.e., the hybrid flow-shop (HFS) is not significant for resulting values of maximum flowtime and PC = 2 is not significant for mean flowtime. More important to our study, the *FIT* factor was found to be highly significant for %tardy and mean flowtime, supporting *H2S* and suggesting, when also considering results from Fig. 4, that the fits that we proposed do have an influence on performance. Moreover, the estimate for *FIT* is negative for %tardy and mean flowtime, suggesting that a good fit between ME and PC reduced the values of %tardy and mean flowtime, i.e., increased performance.

It is worth mentioning that ME = flow-shop and PC = 1 are not shown because they are the base values for ME and PC, and do not provide additional information to the model.

Table 6
ANOVA tests of the significance of single factors and their interactions.

\Response	%Tardy		Mean flowtime		Mean lateness		Max flowtime	
Factor	F value	Pr(>F)	F value	Pr(>F)	F value	Pr(>F)	F value	Pr(>F)
ρ	16,740	0.0000	8027	0.0000	7034	0.0000	1896	0.0000
TWK	3566	0.0000	0	0.4820	51	0.0000	0	0.8280
ME	379	0.0000	4782	0.0000	3233	0.0000	1195	0.0000
PC	815	0.0000	356	0.0000	5	0.0268	43	0.0000
ρ*TWK	102	0.0000	0	0.5690	18	0.0000	0	0.8300
ρ*ME	11	0.0007	1717	0.0000	2476	0.0000	977	0.0000
TWK*ME	51	0.0000	1	0.4000	77	0.0000	0	0.8960
ρ*PC	455	0.0000	221	0.0000	0	0.7521	37	0.0000
TWK*PC	3	0.0763	0	0.8720	59	0.0000	0	0.9600
ME*PC	**448**	**0.0000**	**241**	**0.0000**	**6**	**0.0171**	**119**	**0.0000**
ρ*TWK*ME	21	0.0000	1	0.4690	40	0.0000	0	0.9010
ρ*TWK*PC	21	0.0000	0	0.8960	49	0.0000	0	0.9610
ρ*ME*PC	211	0.0000	161	0.0000	0	0.7379	97	0.0000
TWK*ME*PC	1	0.4158	0	0.8470	60	0.0000	0	0.9760
ρ*TWK*ME*PC	45	0.0000	0	0.8680	48	0.0000	0	0.9770

ρ = mean utilisation factor of all machines, TWK = Due-date tightness, ME = machine environment, PC = policy complexity.

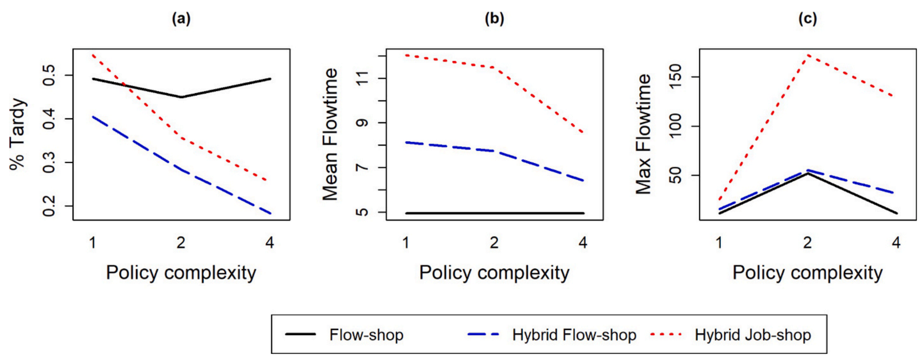

Fig. 4. Interaction plots regarding the effects of machine environment on performance.

6. Discussion

The environmental characteristics of what Wiers and Van der Schaaf (1997) classified as a stress shop causes this shop-floor environment to be the most fitting environment to implement and utilise a cyber-physical shop-floor. The combination of low specificity of the production processes with high production task complexity and moderate dynamism is an environment that could be highly benefited from the automated, supervised, controlled and interconnected organisational structure that a CPSF provides because advanced scheduling and sequencing methodologies could be seamlessly used in this technological environment.

By being able to manage a complex market environment with the best scheduling solutions, stress shops with CPS capabilities will gain competitive advantage as their customer requirements, such as, short and exact delivery dates, low costs (caused by reduced work-in-process inventories), and quality assurance, will be satisfied.

On the other hand, the market requirements and the low scheduling task complexity of smooth, socio-technical and social shops do not impose managers with high scheduling standards, which could result in minimal impact on the performance of the shop-floor from implementing a CPS, as suggested by Fig. 3 (a). This minimal impact in performance increase, compared with the very high costs of CPSF implementation, could result in a bad investment for these firms.

It is worth noting that this paper is centered only on studying which type of shop-floor environment could benefit the most from using the capabilities of a CPS and is not concerned with a wider focus, such as a supply chain point of view. We think that cyber-phyisical systems are a technology that could prove useful for every type of supply chain strategic context but that the promise of gaining competitive advantage through the implementation of CPS made by the Industry 4.0 initiative (Kagermann et al., 2013) could fall short for certain shop-floor environments.

As the technologies of CPSF and the Industry 4.0 initiative mature

Table 7
Regression analysis regarding ME, PC and *FIT* considering various responses.

Coefficient values	%Tardy		Mean flowtime		Mean lateness		Max flowtime	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
(Intercept)	−4.1252	0.0000	−51.2942	0.0000	−2998.06	0.0000	−873.39	0.0000
ρ	0.0539	0.0000	0.6332	0.0000	34.81	0.0000	9.51	0.0000
ME = HFS[a]	−0.2030	0.0000	2.7647	0.0000	48.98	0.0000	6.45	0.1027
ME = HJS	−0.1259	0.0000	6.0206	0.0000	257.46	0.0000	92.57	0.0000
PC = 2	−0.1224	0.0000	−0.2653	0.0782	47.17	0.0000	75.10	0.0000
PC = 4	−0.1808	0.0000	−1.7394	0.0000	−16.28	0.0777	39.51	0.0000
FIT	−0.0458	0.0000	−0.7668	0.0000	−13.74	0.0547	6.57	0.0567

[a]HFS = hybrid flow-shop, HJS = hybrid job-shop.

into a consolidated field where more actual implementations of CPSF exist, researchers could use our proposed experimental design (see subsection 5.2) to prove and analyse whether this proposed fit is true or not and whether stress shops could benefit the most from implementing CPSF in empirical settings.

Additionally, results presented in subsection 5.3 provide motivation to further study *H1* as the interaction between machine environment, associated with the shop-floor environment factor, and policy complexity, associated with the CPSF implementation level factor, was found to be significant, supporting the statement of *H1S*. Similarly, results shown in Fig. 4 (a) and (b) suggest that the performance of smooth shops, represented in this study by the simple flow-shop environment, is not highly affected by a change in policy complexity. On the contrary, the performance of stress and socio-technical shops, represented by the hybrid flow-shop and hybrid job-shop environments, respectively, was highly influenced by a change in policy complexity.

Interestingly, the behaviour of both the hybrid flow-shop and hybrid job-shop in Fig. 4 (a) is similar to the conjectured behaviour presented in Fig. 3 (a) regarding the behaviour of socio-technical shops. In addition, the behaviour of the hybrid flow-shop and hybrid job-shop environments in Fig. 4 (b) is similar to the conjectured behaviour shown in Fig. 3 (a) regarding the behaviour of stress shops.

Furthermore, results from the regression analysis suggest that the fits proposed in this study are significant in the simulated performance of shop-floors, showing support for *H2S*. Therefore, since statistical tests show support for *H1S* and *H2S* we can conclude that there is motivation to further study the assertions of *H1* and *H2* in future studies considering an empirical approach.

6.1. Limitations of the study and future research

The most evident limitation of this study is the fact that it did not provide direct evidence to support the main hypotheses of the study due to the lack of use of different scheduling approaches, supported by CPSF capabilities, in different shop-floor environments. Despite this limitation, this study did provide support to the surrogate hypotheses and it is the first study to investigate, even in a simulated setting, the interaction that machine environments and policy complexities have regarding the performance of a shop-floor and the influence that a good fit between these two factors have on performance improvement.

Another limitation is the lack of absolute correspondence between the conjectured behaviour shown in Fig. 3 (a) and simulation results from Fig. 4 (a) and (b), which has been caused by the experimental design of the study because only WLC and sequencing policies were considered for all machine environments, instead of applying the recommended scheduling approaches from Table 3. Consequently, since WLC/sequencing is a scheduling approach that is more fitting for socio-technical shops, the potential performance improvements from using a fitting scheduling approach, as suggested by Table 3, could be bigger and could correspond more closely to the expected results from Fig. 3. Not all fitting scheduling approaches were used in these preliminary simulation experiments as we wanted directly comparable results by using the same scheduling approach throughout all the machine environments. Therefore, more experimental studies that include all the relevant scheduling approaches suggested in Table 3 are needed.

It is worth noting that the conjectured results presented in subsection 5.2 are only assumptions, especially the expectation regarding the costs of CSPF investment/implementation and the costs of customer dissatisfaction, since these costs could have a different behaviour in real implementation scenarios, e.g., they could be non-linear or could be dependent on the manufacturing environment.

Furthermore, the shop-floor environments considered in subsection 5.3 are simplified models of real shop-floors. More studies that consider real manufacturing scenarios that accurately model the characteristics of each manufacturing context with their corresponding constraints, e.g., sequence-dependent setup times, are needed to further study this topic.

Finally, to comprehensively study the fit between CPS and manufacturing contexts using empirical evidence from real shop-floors, a mature field regarding the implementation of CPSF is needed. Thus, the development of studies that thoroughly apply the proposed experimental design presented in subsection 5.2 will depend on the speed in which the manufacturing sector implements full CPSF and uses these capabilities as support to carry out the scheduling task.

7. Conclusions

This paper focused on discussing whether CPS capabilities could result in a competitive advantage for manufacturing companies by significantly increasing their performance, upsetting the costs of investing in a CPSF implementation, through a good fit between the level of implementation of a cyber-physical shop-floor and the manufacturing context.

After a description of what a cyber-physical shop-floor entails, how it can support the scheduling task, and a characterisation of different manufacturing contexts, the fit between stress-shops and a full CPSF implementation was proposed by identifying, through deductive reasoning, the shop floor's contextual factors creating the scheduling needs that could only be solved by a full implementation of a cyber-physical shop-floor. Furthermore, we set forth an experimental design to assess the applicability of the proposed fit, anticipating for a future scenario where empirical analyses can be carried out.

However, as the current industrial environment is not mature enough to perform empirical studies regarding complete CPS capabilities, a preliminary simulation experiment was carried out to assess whether different scheduling complexities have an impact on the performance of particular manufacturing contexts. Experimental results showed that using more complex scheduling techniques will not produce a significantly better performance in simple flow-shops. On the contrary, the performance of both hybrid flow-shops and hybrid job-shops was highly influenced by the complexity of the scheduling technique, which suggests that installing CPS capabilities could be beneficial for more complex manufacturing contexts.

The resulting statistical significance of the interaction between scheduling approach complexities and machine environments as well as the influence of the fit between these two factors on shop-floor performance of these preliminary simulation experiments provide motivation to further study the applicability of the proposed fit between stress shops and a full CPSF implementation level through comprehensive empirical studies, as this is the first study to question the universal applicability of CPS capabilities.

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References

Ahmad, S., Schroeder, R.G., 2002. Refining the product-process matrix. Int. J. Oper. Prod. Manag. 22, 103–124. https://doi.org/10.1108/01443570210412097.

Allahverdi, A., Ng, C.T., Cheng, T.C.E., Kovalyov, M.Y., 2008. A survey of scheduling problems with setup times or costs. Eur. J. Oper. Res. 187, 985–1032. https://doi.org/10.1016/j.ejor.2006.06.060.

Alqahtani, A.Y., Gupta, S.M., Nakashima, K., 2019. Warranty and maintenance analysis of sensor embedded products using internet of things in industry 4.0. Int. J. Prod. Econ. 208, 483–499. https://doi.org/10.1016/j.ijpe.2018.12.022.

Ayvarnam, N., Mayurappriyan, P.S., 2017. Dynamic scheduling of machines towards the vision of industry 4.0 studio—A case study. In: Deiva Sundari, P., Dash, S.S., Das, S., Panigrahi, B.K. (Eds.), Proceedings of 2nd International Conference on Intelligent Computing and Applications: ICICA 2015. Springer Singapore, Singapore, pp. 103–111. https://doi.org/10.1007/978-981-10-1645-5_9.

Bagchi, T.P., Gupta, J.N.D., Sriskandarajah, C., 2006. A review of TSP based approaches for flowshop scheduling. Eur. J. Oper. Res. 169, 816–854. https://doi.org/10.1016/j.ejor.2004.06.040.

Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manag. 17, 99–120. https://doi.org/10.1177/014920639101700108.

Bergamaschi, D., Cigolini, R., Perona, M., Portioli, A., 1997. Order review and release strategies in a job shop environment: a review and a classification. Int. J. Prod. Res. 35, 399–420. https://doi.org/10.1080/002075497195821.

Blackstone, J.H., Phillips, D., Hogg, G., 1982. A state-of-the-art survey of dispatching rules for manufacturing job shop operations. Int. J. Prod. Res. 20, 27–45. https://doi.org/10.1080/00207548208947745.

Branke, J., Nguyen, S., Pickardt, C.W., Zhang, M., 2016. Automated design of production scheduling heuristics: a review. IEEE Trans. Evol. Comput. 20, 110–124. https://doi.org/10.1109/TEVC.2015.2429314.

Breithaupt, J.-W., Land, M., Nyhuis, P., 2002. The workload control concept: theory and practical extensions of Load Oriented Order Release. Prod. Plan. Control 13, 625–638. https://doi.org/10.1080/0953728021000026230.

Cheng, Y., Farooq, S., 2018. The role of plants in manufacturing networks: a revisit and extension. Int. J. Prod. Econ. 206, 15–32. https://doi.org/10.1016/j.ijpe.2018.09.001.

Christensen, W.J., Germain, R.N., Birou, L., 2007. Variance vs average: supply chain lead-time as a predictor of financial performance. Suppl. Chain Manag. 12, 349–357. https://doi.org/10.1108/13598540710776926.

Dalenogare, L.S., Benitez, G.B., Ayala, N.F., Frank, A.G., 2018. The expected contribution of Industry 4.0 technologies for industrial performance. Int. J. Prod. Econ. 204, 383–394. https://doi.org/10.1016/j.ijpe.2018.08.019.

Devaraj, S., Hollingworth, D.G., Schroeder, R.G., 2001. Generic manufacturing strategies: an empirical test of two configurational typologies. J. Oper. Manag. 19, 427–452. https://doi.org/10.1016/S0272-6963(01)00046-8.

Framinan, J.M., Ruiz, R., 2010. Architecture of manufacturing scheduling systems: literature review and an integrated proposal. Eur. J. Oper. Res. 205, 237–246. https://doi.org/10.1016/j.ejor.2009.09.026.

Frank, A.G., Dalenogare, L.S., Ayala, N.F., 2019. Industry 4.0 technologies: implementation patterns in manufacturing companies. Int. J. Prod. Econ. 210, 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004.

Fredendall, L.D., Ojha, D., Patterson, J.W., 2010. Concerning the theory of workload control. Eur. J. Oper. Res. 201, 99–111. https://doi.org/10.1016/j.ejor.2009.02.003.

Fuchigami, H.Y., Rangel, S., 2017. A survey of case studies in production scheduling: analysis and perspectives. J. Comput. Sci. https://doi.org/10.1016/j.jocs.2017.06.004.

Hayes, R.H., Wheelwright, S.C., 1979. Link manufacturing process and product life cycles. Harv. Bus. Rev. 57, 133–140.

Helkiö, P., Tenhiälä, A., 2013. A contingency theoretical perspective to the product-process matrix. Int. J. Oper. Prod. Manag. 33, 216–244. https://doi.org/10.1108/01443571311295644.

Hendry, L., Huang, Y., Stevenson, M., 2013. Workload control: successful implementation taking a contingency-based view of production planning and control. Int. J. Oper. Prod. Manag. 33, 69–103. https://doi.org/10.1108/01443571311288057.

Hernández, G., Mendoza, J., 2015. Fundamentos y Planeació}n de la Manufactura Automatizada, 1a ed. Pearson, Ciudad de México.

Hitt, M.A., Xu, K., Carnes, C.M., 2016. Resource based theory in operations management research. J. Oper. Manag. 41, 77–94. https://doi.org/10.1016/j.jom.2015.11.002.

Ivanov, D., Dolgui, A., Sokolov, B., Werner, F., Ivanova, M., 2016. A dynamic model and an algorithm for short-term supply chain scheduling in the smart factory industry 4.0. Int. J. Prod. Res. 54, 386–402. https://doi.org/10.1080/00207543.2014.999958.

Johansson, P., Olhager, J., 2006. Linking product–process matrices for manufacturing and industrial service operations. Int. J. Prod. Econ. 104, 615–624. https://doi.org/10.1016/j.ijpe.2005.12.008.

Jonsson, P., Mattsson, S.-A., 2003. The implications of fit between planning environments and manufacturing planning and control methods. Int. J. Oper. Prod. Manag. 23, 872–900.

Kagermann, H., Wahlster, W., Helbig, J., 2013. Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0.

Kelton, W.D., Smith, J.S., Sturrock, D.T., 2014. Simio and Simulation: Modeling, Analysis, Applications, first ed. Simio LLC, Sewickley, PA.

Kemppainen, K., Vepsäläinen, A.P.J., Tinnilä, M., 2008. Mapping the structural properties of production process and product mix. Int. J. Prod. Econ. 111, 713–728. https://doi.org/10.1016/j.ijpe.2007.03.020.

Kusiak, A., 2018. Smart manufacturing. Int. J. Prod. Res. 56, 1–10. https://doi.org/10.1080/00207543.2017.1351644.

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., Hoffmann, M., 2014. Industry 4.0. Bus. Inf. Syst. Eng. 6, 239–242. https://doi.org/10.1007/s12599-014-0334-4.

Lee, J., Bagheri, B., Kao, H.-A., 2015. A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. Manuf. Lett. 3, 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001.

Li, L., Lee, Y.S., 1994. Pricing and delivery-time performance in a competitive environment. Manag. Sci. 40, 633–646.

Liu, C., Zhang, L., Zhang, D., 2014. Task scheduling in cyber-physical systems. In: 2014 IEEE 11th Intl Conf on Ubiquitous Intelligence and Computing and 2014 IEEE 11th Intl Conf on Autonomic and Trusted Computing and 2014 IEEE 14th Intl Conf on Scalable Computing and Communications and its Associated Workshops, pp. 319–324. https://doi.org/10.1109/UIC-ATC-ScalCom.2014.97.

Lloréns-Montes, F.J., García-Morales, V.J., Verdú-Jover, A.J., 2004. Flexibility and quality management in manufacturing: an alternative approach. Prod. Plan. Control 15, 525–533. https://doi.org/10.1080/09537280410001726339.

Lu, M.-S., Romanowski, R., 2013. Multicontextual dispatching rules for job shops with dynamic job arrival. Int. J. Adv. Manuf. Technol. 67, 19–33. https://doi.org/10.1007/s00170-013-4765-8.

Lu, Y., 2017. Industry 4.0: a survey on technologies, applications and open research issues. J. Ind. Inf. Integr. 6, 1–10. https://doi.org/10.1016/j.jii.2017.04.005.

McCarthy, I.P., Silvestre, B.S., Kietzmann, J.H., 2013. Understanding outsourcing contexts through information asymmetry and capability fit. Prod. Plan. Control 24, 277–283. https://doi.org/10.1080/09537287.2011.648765.

Meyer, H., Fuchs, F., Thiel, K., 2009. Manufacturing Execution Systems (MES): Optimal Design, Planning, and Deployment, first ed. McGraw-Hill, New York.

Mittal, S., Khan, M.A., Romero, D., Wuest, T., 2018. A critical review of smart manufacturing & Industry 4.0 maturity models: implications for small and medium-sized enterprises (SMEs). J. Manuf. Syst. 49, 194–214. https://doi.org/10.1016/j.jmsy.2018.10.005.

Mizrak, P., Bayhan, G.M., 2006. Comparative study of dispatching rules in a real-life job shop environment. Appl. Artif. Intell. 20, 585–607.

Mlinar, T., Chevalier, P., 2016. Dynamic admission control for two customer classes with stochastic demands and strict due dates. Int. J. Prod. Res. 54, 6156–6173. https://doi.org/10.1080/00207543.2015.1055846.

Molina, A., Bell, R., 1999. A manufacturing model representation of a flexible manufacturing facility. Proc. IMechE 213, 225–246. https://doi.org/10.1243/0954405991516723.

Monostori, L., 2014. Cyber-physical production systems: roots, expectations and R&D challenges. Procedia CIRP 17, 9–13. https://doi.org/10.1016/j.procir.2014.03.115.

Morton, T., Pentico, D.W., 1993. Heuristic Scheduling Systems: with Applications to Production Systems and Project Management. Wiley-Interscience, Hoboken, NJ.

Münch, L., Fowler, J.W., Mason, S.J., 2013. Dispatching approaches. In: Münch, L., Fowler, J.W., Mason, S.J. (Eds.), Production Planning and Control for Semiconductor Wafer Fabrication Facilities: Modeling, Analysis, and Systems. Springer New York, New York, NY, pp. 65–104. https://doi.org/10.1007/978-1-4614-4472-5_4.

Nilsen, S., Nyberg, E., 2016. The Adoption of Industry 4.0- Technologies in Manufacturing – a Multiple Case Study. KTH.

Olson, D.L., Chae, B.K., Sheu, C., 2013. Relative impact of different ERP forms on manufacturing organisations: an exploratory analysis of a global manufacturing survey. Int. J. Prod. Res. 51, 1520–1534. https://doi.org/10.1080/00207543.2012.701772.

Philipoom, P.R., Malhotra, M.K., Jensen, J.B., 1993. An evaluation of capacity sensitive order review and release procedures in job shops. Decis. Sci. J. 24, 1109–1134. https://doi.org/10.1111/j.1540-5915.1993.tb00506.x.

Pinedo, M., 2016. Scheduling: Theory, Algorithms and Systems, Fifth. Springer, New York. https://doi.org/10.1007/978-1-4614-2361-4.

Plugge, A., Bouwman, H., 2013. Fit between sourcing capabilities and organisational structure on IT outsourcing performance. Prod. Plan. Control 24, 375–387. https://doi.org/10.1080/09537287.2011.648489.

Raheja, A.S., Subramaniam, V., 2002. Reactive recovery of job shop schedules – a review. Int. J. Adv. Manuf. Technol. 19, 756–763. https://doi.org/10.1007/s001700200087.

Rajendran, C., Holthaus, O., 1999. A comparative study of dispatching rules in dynamic flowshops and jobshops. Eur. J. Oper. Res. 116, 156–170. https://doi.org/10.1016/S0377-2217(98)00023-X.

Ray, S., Jewkes, E.M., 2004. Customer lead time management when both demand and price are lead time sensitive. Eur. J. Oper. Res. 153, 769–781. https://doi.org/10.1016/S0377-2217(02)00655-0.

Romero-Silva, R., Hurtado, M., Santos, J., 2016a. Is the scheduling task context-dependent? A survey investigating the presence of constraints in different manufacturing contexts. Prod. Plan. Control 27, 753–760. https://doi.org/10.1080/09537287.2016.1166274.

Romero-Silva, R., Santos, J., Hurtado, M., 2015. Entornos de programación de la producción en la industria de la manufactura: alineación entre necesidades y métodos. Dyn. Manag. 3, 1–10. https://doi.org/10.6036/MN7717.

Romero-Silva, R., Santos, J., Hurtado, M., 2016. Bridging the gap between scheduling needs and methods. Dyna 91, 124–125. https://doi.org/10.6036/7805.

Romero-Silva, R., Santos, J., Hurtado, M., 2018. A note on defining organisational systems for contingency theory in OM. Prod. Plan. Control 29, 1343–1348. https://doi.org/10.1080/09537287.2018.1535146.

Romero-Silva, R., Santos, J., Hurtado, M., 2015a. A framework for studying practical production scheduling. Prod. Plan. Control 26, 438–450. https://doi.org/10.1080/09537287.2014.919413.

Ronconi, D., Birgin, E.G., 2012. Mixed-integer programming models for flowshop scheduling problems minimizing the total earliness and tardiness. In: Ri-os-Mercado, R.Z., Ri-os-Soli-s, Y.A. (Eds.), Just-in-Time Systems. Springer New York, New York, NY, pp. 91–105. https://doi.org/10.1007/978-1-4614-1123-9_5.

Rossit, D.A., Tohmé, F., Frutos, M., 2018. Industry 4.0: smart scheduling. Int. J. Prod. Res. 0, 1–12. https://doi.org/10.1080/00207543.2018.1504248.

Ruiz, R., Maroto, C., 2005. A comprehensive review and evaluation of permutation flowshop heuristics. Eur. J. Oper. Res. 165, 479. https://doi.org/10.1016/j.ejor.2004.04.017.

Salimian, H., Rashidirad, M., Soltani, E., 2017. A contingency view on the impact of supplier development on design and conformance quality performance. Prod. Plan. Control 1–11. https://doi.org/10.1080/09537287.2017.1282056.

Scheuermann, C., Verclas, S., Bruegge, B., 2015. Agile factory - an example of an industry 4.0 manufacturing process. In: 2015 IEEE 3rd International Conference on Cyber-Physical Systems, Networks, and Applications, pp. 43–47. https://doi.org/10.1109/CPSNA.2015.17.

Schlechtendahl, J., Keinert, M., Kretschmer, F., Lechler, A., Verl, A., 2015. Making existing production systems Industry 4.0-ready. Prod. Eng. 9, 143–148. https://doi.org/10.1007/s11740-014-0586-3.
Shi, J., Wan, J., Yan, H., Suo, H., 2011. A survey of cyber-physical systems. In: 2011 International Conference on Wireless Communications and Signal Processing (WCSP), pp. 1–6. https://doi.org/10.1109/WCSP.2011.6096958.
Slack, N., 1982. Work time distributions in production system modelling. https://doi.org/10.1002/9781118785317.weom100178.
Slotnick, S.A., 2011. Order acceptance and scheduling: a taxonomy and review. Eur. J. Oper. Res. 212, 1–11. https://doi.org/10.1016/j.ejor.2010.09.042.
Sousa, R., Voss, C.A., 2008. Contingency research in operations management practices. J. Oper. Manag. 26, 697–713. https://doi.org/10.1016/j.jom.2008.06.001.
Suwa, H., Sandoh, H., 2013. When-to-Revise against uncertainty? In: Suwa, H., Sandoh, H. (Eds.), Online Scheduling in Manufacturing: A Cumulative Delay Approach. Springer London, London, pp. 41–54. https://doi.org/10.1007/978-1-4471-4561-5_3.
Taylor, A., Taylor, M., 2014. Factors influencing effective implementation of performance measurement systems in small and medium-sized enterprises and large firms: a perspective from Contingency Theory. Int. J. Prod. Res. 52, 847–866. https://doi.org/10.1080/00207543.2013.842023.
Tenhiälä, A., 2011. Contingency theory of capacity planning: the link between process types and planning methods. J. Oper. Manag. 29, 65–77. https://doi.org/10.1016/j.jom.2010.05.003.
Tenhiälä, A., Helkiö, P., 2015. Performance effects of using an ERP system for manufacturing planning and control under dynamic market requirements. J. Oper. Manag. 36, 147–164. https://doi.org/10.1016/j.jom.2014.05.001.
Terekhov, D., Down, D.G., Beck, J.C., 2014. Queueing-theoretic approaches for dynamic scheduling: a survey. Surv. Oper. Res. Manag. Sci. 19, 105–129. https://doi.org/10.1016/j.sorms.2014.09.001.
The R Foundation, 2016. The R Project for Statistical Computing.
van der Schaaf, T., 1995. Human recovery of errors in man-machine systems. In: IFAC Proceedings Volumes, pp. 71–76. https://doi.org/10.1016/S1474-6670(17)45211-6.
Vieira, G.E., Herrmann, J.W., Lin, E., 2003. Rescheduling manufacturing systems: a framework of strategies, policies, and methods. J. Sched. 6, 39–62. https://doi.org/10.1023/A:1022235519958.
Wang, L., Törngren, M., Onori, M., 2015. Current status and advancement of cyber-physical systems in manufacturing. J. Manuf. Syst. 37, 517–527. https://doi.org/10.1016/j.jmsy.2015.04.008.
Weill, P., Olson, M.H., 1989. An assessment of the contingency theory of management information systems. J. Manag. Inf. Syst. 6, 59–85.
Welch, P.D., 1983. The statistical analysis of simulation results. In: Lavenberg, S.S. (Ed.), The Computer Performance Modeling Handbook. Academic Press, New York, pp. 268–328.
Weyer, S., Schmitt, M., Ohmer, M., Gorecky, D., 2015. Towards Industry 4.0 - standardization as the crucial challenge for highly modular, multi-vendor production systems. IFAC-PapersOnLine. https://doi.org/10.1016/j.ifacol.2015.06.143.
Wiers, V.C.S., der Schaaf, T. Van, 1997. A framework for decision support in production scheduling tasks. Prod. Plan. Control 8, 533–544.
Wright, P., 2014. Cyber-physical product manufacturing. Manuf. Lett. 2, 49–53. https://doi.org/10.1016/j.mfglet.2013.10.001.
Yin, Y., Stecke, K.E., Li, D., 2018. The evolution of production systems from Industry 2.0 through Industry 4.0. Int. J. Prod. Res. 56, 848–861. https://doi.org/10.1080/00207543.2017.1403664.
Zhang, X., Chen, R., Ma, Y., 2007. An empirical examination of response time, product variety and firm performance. Int. J. Prod. Res. 45, 3135–3150. https://doi.org/10.1080/00207540600786707.